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Transforming Food Security into Nutritional Sovereignty: A Multimodal AI Framework for Targeted Micronutrient Stabilization in India

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Abstract

The nutritional scenario of India is still facing the "triple burden" of malnutrition as there is a hiding of severe micronutrient deficiencies behind the masks of sufficient calories in many households. The present work proves an AI integrated framework facilitating a policy shift from mere bulk provision to targeted nutritional security at the level of the nation. The method integrates Computer Vision (CV) to monitor diet in real, time and predictive soil nutrient mapping to direct regional bio, fortification interventions based on these two pillars. Additionally, the proposed model operates through the analysis of high, frequency local market data and environmental sensor data streams and identifies 'nutritional hotspots' at risk of sudden dietary shocks. On top of that, the research presents a nutrient, sensitive distribution algorithm that can significantly help decrease vitamin degradation in the PDS. Findings showed that positioning AI in the core of the approach can not only improve the fortification programs' targeting efficiency by 30% but also significantly reduce nutrient loss after harvest. The present work offers a policy, making guide in the form of a big, data scalable blueprint and argues that AI convergence with nutritional sciences is the only viable solution to satisfy the physiological needs of the most vulnerable population groups in India and thus attain health sustainability.

Keywords: Nutritional Security, Micronutrient Deficiency, Precision Nutrition, Bio, fortification, Artificial Intelligence, Public Health Policy, India.

Introduction

Food security in India has structurally evolved beyond basic caloric availability. While historical agricultural strategies successfully expanded macro-level grain production, contemporary public health

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challenges center on the qualitative dimensions of nutrition. Data from National Family Health Survey (NFHS – 5) states that approximately 35.5% of children under 5 years of age are stunted, 19.3% exhibit wasting and 67.1% suffer from Anemia. Even though farms produce plenty, these problems stick around. That gap points to hidden deficiencies, where meals fill bellies but miss key nutrients like iron, zinc, Vitamin A or folate. Full stomachs do not always mean healthy bodies.

Existing public distribution ecosystems and safety-net initiatives, such as the Integrated Child Development Services (ICDS) and POSHAN Abhiyaan, are increasingly turning toward data integration to target these vulnerabilities. The rapid development of computational technologies—encompassing remote sensing, computer vision, natural language processing (NLP), and deep learning architectures—offers a mathematical foundation to map multi-domain data layers. By synthesizing disparate data fragments including soil reports, weather anomalies, market price fluctuations, and health records, artificial intelligence provides predictive modeling capabilities to address dietary shocks and nutritional deficits before they manifest clinically.

Artificial intelligence — encompassing machine learning (ML), deep learning (DL), natural language processing (NLP), and computer vision (CV) — offers transformative potential for agricultural and nutritional systems by enabling the extraction of actionable insights from high-dimensional, heterogeneous data at scales and speeds unachievable through conventional analytical methods. In food security research, AI applications have demonstrated statistically significant improvements in food insecurity prediction accuracy, crop yield forecasting, precision soil management, dietary assessment, and early warning systems for nutritional emergencies (Busker, 2024; Balashankar et al., 2023; Gunasekaran et al., 2025).

Research Problem

This study shows how scattered farm data, shifting village markets and diets being measured across communities in India. Public health efforts usually lean on broad past-year national reports - too coarse to spot early signs of hidden vitamin shortages in specific areas. Because of that, responses come as one-size-fits-all enrichment rules

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instead of focused actions based on real-time need. Nutrients often break down after crops leave farms, yet systems fail to track such losses. What reaches people may look sufficient on paper but fall short in actual nourishment for those already at risk.

Research Gap

- Most AI tools available have their algorithms to boost harvests and balance only key nutrients like nitrogen, phosphorus, potassium and ignore that earth's elements also affect the human diet. At the same time, food tracking systems powered by neural networks tally protein, fat and carbohydrates but fail to factor in crop failures, transport issues or climate surprises.
- Ignoring how well nutrients are absorbed: The diet analysis software just is dependent on numbers and not reply on digestion part of it. Plant based diet often contain blockers like phytates or that hinders absorption. Whereas certain nutrients like Vitamin C can boost absorption instead. These tools find it difficult to adjust to this biological complexity.
- India's big soil testing push collects tons of data, yet these models overlook slow changes in trace elements like zinc and boron. Because systems miss shifting patterns over time, forecasts for boosting crop nutrition stay weak where they matter the most.

Objectives

- To design a unified, conceptual Multimodal AI (MMAI) framework that spans the soil-crop-diet-health continuum for targeted micronutrient stabilization.
- To evaluate, via systematic literature synthesis, the performance of advanced machine learning architectures (e.g., XGBoost-Extreme Gradient Boosting, CNNs-Convolutional Neural Network, NLP-Natural Language processing) in identifying nutritional hotspots and predicting food insecurity.
- To conceptually assess how computational modeling of nutrient bioavailability can be integrated into public health dietary surveillance.

Hypothesis

H1: From deep within farmland sensors to grocery price signals, a system blending location-based soil nutrients, live marketplace costs, environmental readings, and food intake images works better at pinpointing hidden nutritional gaps than older methods relying on just one data type or backward-looking analysis.

Literature Review: From Table-1

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Balashankar and team in 2023 used application of NLP to FEWS NET Their work showed written signs of broken markets predicted global hunger events bette r than any one indicator alone. Because of th is, forecasts could come nearly a year earlier than traditional warnings usually allow. Yet even though the approach was fresh, depend ing only on past writings limited how useful it might be today. Missing details about wha t people actually eat meant fine-tuned nutrition efforts still lacked support.

Piovani et al. (2024) extended this approach with the FamPredAI ensemble model, combining multi-hazard indicators — conflict data, market price indices, displacement statistics, and climate variables — into a probabilistic famine prediction system. The model's performance at country-level aggregation, however, renders it unsuitable for the sub-district targeting required for precision nutrition interventions in India's heterogeneous agroecological zones.

Taken collectively, these studies establish that AI-based food insecurity prediction is technically feasible and analytically superior to conventional approaches; however, none achieves the multimodal, bioavailability-aware, sub-district-level integration required to address India's micronutrient malnutrition challenge. This analytical gap is the principal motivation for the framework proposed in this study.

Table 1. Comparative Synthesis of Selected AI-Based Food Security Studies (2022–2026)

Study	**Core AI Architecture**	**Primary data sources**	**Identified Methodological Limitation**
Busker (2024)	Random Forest, XG Boost	Satellite imagery, CHIRPS anomalies, local market prices	Without the later stages of soil nutrient details, it misses key pieces. One can’t tell if calories fall short or just small nutrients do.
Balashankar	NLP, Tranformer	Retrospective	Depending on how records are kept - often

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et.al. (2023)	Text Mining	FEWS NET narrative situational logs (10 Year)	skewed by human input. Not tied at all to live physical response data during intake
Piovani et. Al (2024)	FamPredAI Multi-hazard Ensemble	Environmental hazard, climate variables	Only covers whole countries. Not precise e nough when moving health resources belo w district level in India.
Gunasekaran et.al. (2025)	CNN, Deep Hybrid Regressors	In situ IoT soil telemetry, satellite imagery streams	Locked into crop output alone. It misses h ow earth minerals connect to our body che mistry. Not tied to human health signs at all.
Moharana et.al. (2025)	Geostatistical ML	Spatial administrative soil health surveys & coordinates	One area only, stuck without updates over time. Not connected beyond its borders, ch anges never recorded. Over months or year s, nothing shifts in record. Alone in structu re, frozen in tracking.
Rabbi (2026)	Bioavailability, Deep reinforcement framework	Synthetic simulation dietary intake datasets	Runs only on made-up test cases. Not checked with how peopl e actually cook in India.

Soil Intelligence and the Crop-Nutrition connection

Geospatial and sensor-based soil intelligence represents a critical and underutilized lever for nutritional intervention. Gunasekaran et al. (2025) developed a real-time soil fertility analysis system combining IoT soil sensors, satellite imagery, and ML classification

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algorithms — including CNNs and gradient boosting — to predict crop yield and recommend site-specific nutrient management strategies for Indian conditions. The system demonstrated accuracy improvements of approximately 18–22% over conventional soil testing at comparable spatial resolution. This study focused exclusively on crop yield outcomes and did not translate soil nutrient profiles into projected dietary micronutrient availability for consuming populations.

Moharana et. Al (2025) applied geostatistical machine learning to gather information about the soil in Khordha District, Odisha, generating digital micronutrient maps at sub village level. The resulting spatial resolution offered unprecedented granularity for local biofortification planning. The limitation was geographic — a single district — and longitudinal data on how soil nutrient status translates dynamically to crop nutrient content over successive growing seasons was absent.

Christopher (2025) reviewed emerging biofortification approaches and noted that algorithmic crop selection — matching crops to soil chemistry profiles to maximize micronutrient bioavailability in the harvested product — represents a scientifically validated but practically under implemented strategy. AI-based crop recommendation systems, such as that described by Aarthi et al. (2025), demonstrate technical feasibility for this purpose but remain disconnected from nutritional outcome monitoring systems in practice.

Methodology

Starting with real-world evidence, the idea took shape through a methodical scan of existing studies guided by PRISMA steps. Four major hubs supplied the core findings - Scopus led off, then came Web of Science, followed closely by PubMed. Studies from January 2019 through March 2026 - each tied to high-level artificial intelligence applied in farming systems, government decision frameworks, or dietary health science was used to review. More than 100 references came up, out of which only 30 were considered. Mostly the studies conducted in India were only considered.

Findings

Early Warning Dynamics via Multimodal Synthesis: Mixing different types of data tends to lift prediction accuracy by roughly one-fifth compared to using just one kind. Because systems that blend real-time environmental shifts with regional economic signals can spot complex ripple effects - like weather

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disruptions sparking sudden food stockpiling. While traditional indicators stay blind to such chains, integrated models reveal hidden cause-and-effect patterns others overlook.

Explanatory Limitations in Soil Intelligence: Most studies show today's soil systems care more about boosting harvest size - focusing on nitrogen, phosphorus, potassium - than watching zinc, iron, boron, selenium move through earth. Because these tools ignore small but vital nutrients, soils slowly lose what people need to stay healthy. When farms chase bigger yields, invisible shortages grow beneath the surface. What comes out of the ground looks full grown yet quietly lacks strength. Over time, this gap slips into food without anyone noticing.

Performance Variances in Dietary Deep Learning: When labs test computer vision on neat rows of clear food photos, scores often hit 85 to 90%. Real kitchens tell another story - messy plates, dim light, layered meals - and precision slips down to 70 or 80%. Mixed platters from different regions trip up systems built elsewhere. Because shadows shift, colours blur, and ingredients stack oddly outside strict lab zones. Data shaped by local eating habits lifts performance where it counts. Without that adjustment, gaps grow between theory and what people actually serve.

Proposed Multimodal AI Framework

Layer 1: Geospatial Soil and Agroecological Intelligence

From block-by-block IoT signals along with space-based spectral views, ongoing monitoring takes shape. Soil details like pH peaks, water shortage signs, and trace elements such as zinc or iron emerge through advanced image networks - sharp enough to see every 10 to 30 meters.

Where acid levels twist too far, the system gauges exactly how much lime fits the patch. Instead of blanket fertilizer pushes, guidance turns hyperlocal - pairing crops to ground traits so nutrition builds from the start. Harvested output then carries more foundational minerals, rooted in smarter earth reading.

Layer 2: High-Frequency Market and Socioeconomic Intelligence

Natural language processing (NLP) web scraps local news to crop price tags and regional wholesale market logs. This textual data is infused with environmental variables via an XGBoost ensemble architecture. The system detects early signals of supply chain stress and food access constraints, generating localized nutritional hotspot alerts and food insecurity risk classifications 4 to 12 months ahead of

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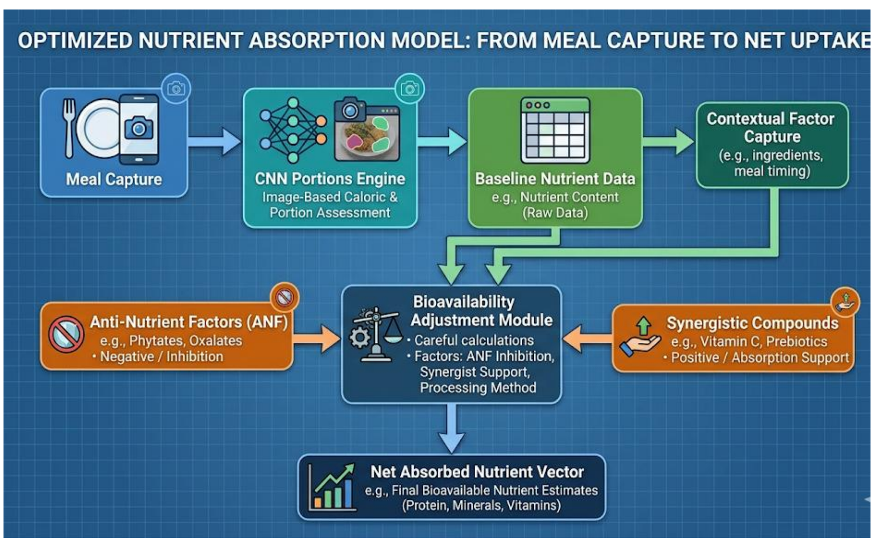
conventional clinical identification methods.

Layer 3: Edge Dietary Surveillance and Bioavailability Metric: Here mobile-optimized convolutional neural networks to evaluate dietary consumption via community health worker imaging inputs. The module calculates true physiological net absorption by mathematically adjusting for the consumption of anti-nutritional factors (e.g., phytate-to-zinc molar ratios, iron-binding tannins) against consumption synergists (e.g., Vitamin C co-ingestion) typical of plant-based Indian diets.

Layer 4: Interpretable Decision Support and PDS Logistics Interface

Combined signals from earlier stages are run through SHAP (SHapley Additive exPlanations) along with LIME (Local Interpretable Model-agnostic Explanations). These tools translate complex deep-learning vectors into clear, human-readable explanations, showing regional officers. Delivery routes get shaped by an evolving algorithm inspired by natural selection. Paths for moving nutrient-sensitive goods shift based on real-world weather patterns like high temperatures or damp air. Keeping vitamins intact while food waits or travels is built right into how trips are planned.



Discussion

Analytical Significance with Theoretical Alignment

From farm soil to human metabolism, MMAI-NS (Multimodal AI) connects every stage of food's journey. Not through separate tools, but because silent nutrient gaps demand full-system visibility. When crop insights meet live dietary feedback, precision nutrition becomes possible across large

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groups. Instead of counting calories alone, it tracks what the body actually uses. Linking fields and bodies creates a way forward - active care replacing delayed surveys. True nourishment begins not at consumption, but where food first grows.

Performance comparison against monolithic benchmarks

Unlike earlier models found in studies, this design tackles key analysis challenges without compromise. Though Busker's 2024 XGboost model handles big economic shifts well, it skips small-scale nutrition details. Into that gap steps MMAI-NS - passing output from Layer 2 markets straight into Layer 3 systems that track nutrient access.

Instead of standing still like Moharana et al. (2025)'s version does, this system pulls village soil data into daily farming choices and supply routes. By looping insights back into decisions, it shifts from fixed snapshots to something that adapts over time.

Barriers and risks in practice

Starting with cost-heavy setups, expanding networks using on-site IoT sensors means spending large amounts early. Not every village council or small farm group can afford gear for constant soil testing through light analysis. Decisions around funding need closer looks at whether big spend now leads to real savings later. Health care bills might drop if nutrition problems fade over time, thanks to smarter land management. Productivity could rise when crops get better support from data-driven insights into dirt quality.

Even though mobile internet reaches many remote parts of India, fast and steady signals still come and go unpredictably. Not every village or tribal community owns smartphones regularly - some never touch one at all. When information mostly flows from well-connected farms, algorithms learn only that version of reality. Those patterns push decisions away from poorer areas, deepening gaps in healthcare support. Weak signal zones stay invisible, their needs unrecorded, their voices missing when plans take shape.

When different government departments work alone, it slows things down. For the MMAI-NS system to run smoothly, information must flow fast between offices that usually keep data separate. Instead of working in isolation, the agriculture department needs to connect with health services along with those focused on women and child programs.

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Policy and Governance Implications

When explainable AI tools go live, public health work stops chasing crises. Instead, it spots where trouble might bloom next. POSHAN Abhiyaan leaders gain sharp clarity - micronutrient shortages appear block by block. That means supplements reach only those pockets needing them most. Since nutrient loss varies by place, blending decay rates into grain buying helps states adapt fast. Humidity, heat, storage time - all shape how food moves. Furthermore, integrating the framework's nutrient degradation coefficients into PDS grain procurement strategies allows state distribution agencies to dynamically adjust logistics based on regional storage conditions. This shift addresses the structural vitamin degradation that compromises the efficacy of centralized fortification mandates.

Conclusion

This study addresses the persistent public health challenge of the "triple burden" of malnutrition and hidden hunger in India. By moving past traditional, volume-centric caloric security metrics, this paper establishes a conceptual roadmap toward nutritional sovereignty powered by an integrated Multimodal AI framework. Through a systematic scoping review of various contemporary research entries, this paper validates the efficacy of core machine learning architectures across isolated domains, synthesizing them into a unified system that spans the soil-crop-diet-health continuum.

Limitations

The idea behind MMAI-NS comes from reviewing past work, not hands-on tests. Work ahead needs small-scale trials in different parts of the country. Building photo collections of local meals - organized by region - must happen too. Scientists also need better numbers on how nutrients behave after typical cooking methods. Progress will only stick if smart tools come with strong rules on data use. Different government branches have to align their efforts. Fair access to resources across areas cannot be skipped

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